

# Determining ideal sites for a pilot experiment in Colombia to trial new forages in East Africa

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## Introduction

The livelihood of approximately 37 million people of the East African (EA) region is highly dependent on livestock. As the pressure for livestock products heightens with growing populations, already harsh environmental conditions are predicted only to worsen (Fisher et al. 2005; Thornton et al. 2007). In Cali, Colombia, the International Center of Tropical Agriculture (CIAT) is leading a cutting edge new breeding programme by developing improved forage varieties specially designed to succeed in the East African

## Materials and Methods

### Cluster analysis

Characterise environmental zones of East Africa into separate environmental clusters based on the following information associated with each pixel:

- \* Areas of high livestock density (Ramankutty et al., 2008)
- \* Areas of annual precipitation > 700 mm
- \* Qualitative soil data (Hengl et al., 2014)
- \* Environmental data: Annual consecutive days of precipitation > 1mm (**CDD**); Total annual rainfall (**TR**); Annual maximum average rainfall over 5 days (**P5D**); Annual 95<sup>th</sup> percentile of precipitation (**P\_95**); Annual average vapor pressure deficit (**VPD**) (Ruane et al. 2015; Funk et al. 2016).

A distance matrix was generated according to Gower's distance to derive hierarchical clusters.

## Results

**Table 1:** Cluster comparison of the environmental zones of East Africa.

VAR	CLUSTER 1 <i>Medium-bad</i>			CLUSTER 2 <i>Good</i>			CLUSTER 3 <i>Hostile</i>			CLUSTER 4 <i>Medium-good</i>		
	Mean	$\sigma$	Slope	Mean	$\sigma$	Slope	Mean	$\sigma$	Slope	Mean	$\sigma$	Slope
CDD	152.83	20.50	0	71.97	18.09	0	165.9	32.40	1	80.47	20.86	0
TR	966.5	153.38	0.66	1171.9	135	1.21	712.7	160.62	-8.81	884.7	145.95	-7.46
P5D	18	4.19	-0.20	19.82	3.59	0.011	19.26	5.43	-0.089	18.84	4.43	-0.041
P_95	15.35	2.16	-0.019	18.18	2.13	0.062	11.29	4.10	0	14.76	2.59	0
VPD	1.53	0.113	0.01001	1.35	0.086	0.0049	1.48	0.086	0.0098	1.42	0.081	0.0077

† **Cluster 1:** Environment "Medium - Bad", places with a regular total rainfall but with a bad distribution of rainfall throughout the year. **Cluster 2:** Environment "Good", places with good total precipitation and with good distribution throughout the year. **Cluster 3:** "Hostile" environment, places with low total precipitation and poor distribution of rainfall throughout the year. **Cluster 4:** Environment "Medium - Good", places with regular total rainfall and good distribution of this throughout the year.

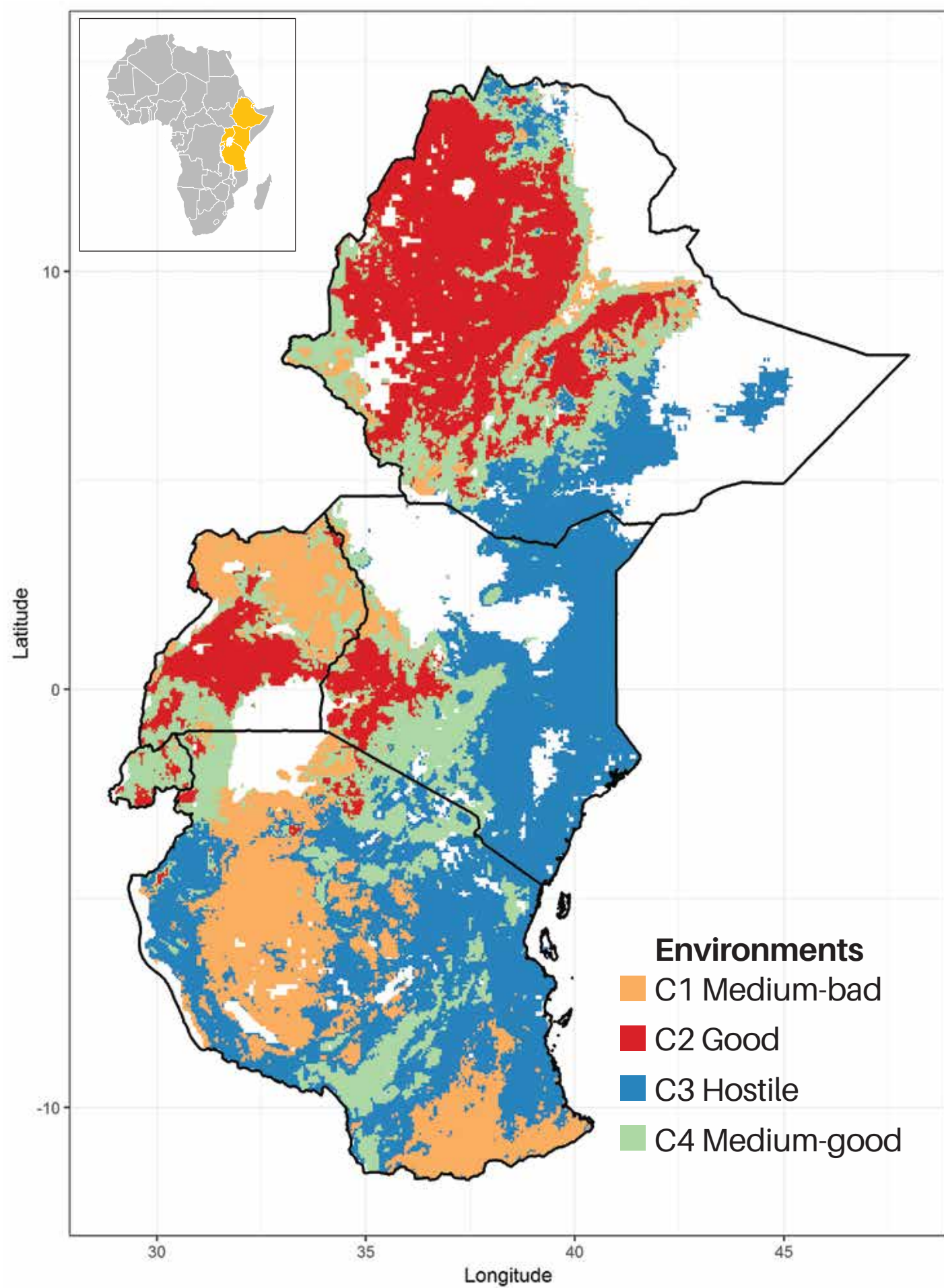
## Discussion and Conclusion

Here, we have presented a highly valuable method for measuring site similarity for future trials that will provide vital information for targeting genotypes to environments. We have successfully selected possible sites in Colombia for the initial testing and first culling of improved forages, which are representative in climate and soil conditions of the four East African clusters. The outcome of this analysis of environments will be compared against analysis of genotype by environment interaction from phenotypic data from each of the identified clusters. Using the entirely free R software, the method can be performed remotely and is easily replicable for other breeding programs and other

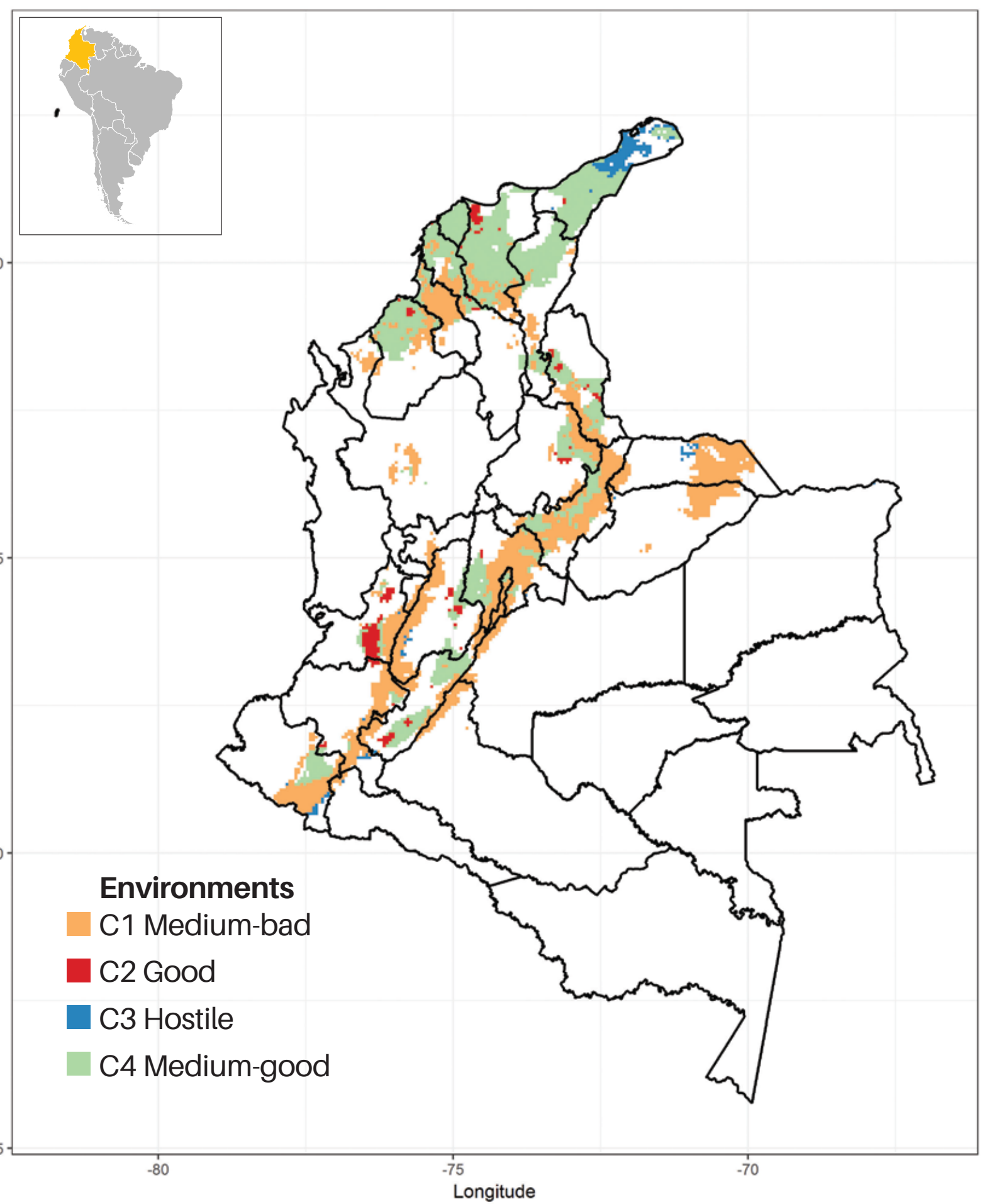
market. Logistic and regulatory constraints make it an infeasible task to test the roughly three thousand hybrids produced in each breeding cycle on-site in East Africa. **Our research shows how to effectively and remotely identify an experimental site in Colombia which can represent the climate and soil conditions existing in East Africa, thereby ensuring that the appropriate abiotic constraints are present in the first selection phase trials.**

### Similarity between Colombia and East Africa

We identified the centroid of each cluster, then the 40 pixels closest to it are located and averaged to obtain the reference. The comparison is developed for each indicator, calculated for time series over thirty years, within the same pixel. Distribution of Dynamic Time Warping Multivariate distances (DTWMD) where obtained for pixels of the Colombian area. The pixels displaying a DTWMD closest to zero (similarity threshold of 20%), are identified as the most similar to the reference pixel. Selected pixels from the Area in Colombia, were used to generate the map of Colombia which detailed possible areas suitable for a pilot experiment. All of the above steps are performed using the free R statistical software.



**Figure 1:** Cluster map of East African region detailing four distance environmental zones.



**Figure 2:** Map of Colombia detailing sites that could be used for a trial experiment based on the 4 EA clusters.

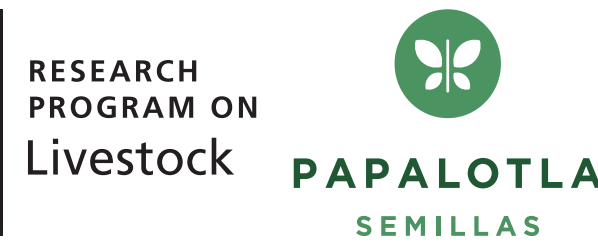
### References

- Alabi TR; Adebola PO; Asfaw A; De Koeyer D; Lopez-Montes A; Asiedu R. 2019. Spatial Multivariate Cluster Analysis for Defining Target Population of Environments in West Africa for Yam Breeding. International Journal of Applied Geospatial Research 10:1–30. doi: [10.4018/IJAGR.2019070104](https://doi.org/10.4018/IJAGR.2019070104)
- Funk C; Peterson P; Landsfeld M; Pedreros D; Verdin J; Shukla S; Husak G; Rowland J; Harrison L; Hoell A; Michaelsen J. 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific Data 2:150066. doi: [10.1038/sdata.2015.66](https://doi.org/10.1038/sdata.2015.66)
- Hengl T; de Jesus JM; MacMillan RA; Batjes NH; Heuvelink GBM; Ribeiro E; Samuel-Rosa A; Kempen B; Leenaars JGB; Walsh MG; Gonzalez MR. 2014. SoilGrids1km — Global Soil Information Based on Automated Mapping. PLoS ONE 9:e105992. doi: [10.1371/journal.pone.0114788](https://doi.org/10.1371/journal.pone.0114788)
- Hyman G; Hodson D; Jones P. 2013. Spatial analysis to support geographic targeting of genotypes to environments. Front. Physiol. 4:40. doi: [10.3389/fphys.2013.00040](https://doi.org/10.3389/fphys.2013.00040)
- Ramankutty N; Evan AT; Monfreda C; Foley JA. 2008. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. Global Biogeochemical Cycles, 22:GB1003. doi: [10.1029/2007GB002952](https://doi.org/10.1029/2007GB002952)

Ruane AC; Goldberg R; Chrysanthacopoulos J. 2015. Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. Agricultural and Forest Meteorology, 200:233–248. doi: [10.1016/j.agrformet.2014.09.016](https://doi.org/10.1016/j.agrformet.2014.09.016)

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